Crude Oil and Stock Markets: Stability, Instability, and Bubbles[1]

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Abstract

We analyze the long-run relationship between the world price of crude oil and international stock markets over 1971:1-2008:3 using a cointegrated vector error correction model with additional regressors. Allowing for endogenously identified breaks in the cointegrating and error correction matrices, we find evidence for breaks after 1980:5, 1988:1, and 1999:9. We find a clear long-run relationship between these series for six OECD countries for 1971:1-1980.5 and 1988:2-1999.9, suggesting that stock market indices respond negatively to increases in the oil price in the long run. During 1980.6-1988.1, we find relationships that are not statistically significantly different from either zero or from the relationships of the previous period. The expected negative long-run relationship appears to disintegrate after 1999.9. This finding supports a conjecture of change in the relationship between real oil price and real stock prices in the last decade compared to earlier years, which may suggest the presence of several stock market bubbles and/or oil price bubbles since the turn of the century.

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1. Introduction

The relationship between oil prices and economic activity has been investigated by a number of researchers. On the issue of the effect of oil price shocks on stock market returns, Jones and Kaul (1996), Sadorsky (1999) and Ciner (2001) report a significant negative connection, while Chen *et al.* (1986) and Huang *et al.* (1996) do not. A negative association between oil price shocks and stock market returns has been reported in several recent papers. Nandha and Faff (2008) find oil prices rises have a detrimental effect on stock returns in all sectors except mining and oil and gas industries, O'Neil *et al.* (2008) find that oil price increases lead to reduced stock returns in the United States, the United Kingdom and France, and Park and Ratti (2008) report that oil price shocks have a statistically significant negative impact on real stock returns in the U.S. and 12 European oil importing countries.[2] In new strands in the literature, Kilian and Park (2007) report that only oil price increases driven by precautionary demand for oil over concern about future oil supplies negatively affect stock prices, and Gogineni (2007) finds that industry stock price returns depends on demand and cost side reliance on oil and on size of oil price changes.

Research on the effect of oil prices on stock prices parallels a larger literature on the connection of oil price shocks with real activity. Much of this research has been influenced by Hamilton's (1983) connection of oil price shocks with recession in the U.S. Hamilton's finding has been elaborated on and confirmed by Mork, (1989), Lee *et al.* (1995), Hooker (1996),

[2] Nandha and Faff (2008) review work on the effect of oil price on equity prices. Recently papers have focused on the effect of oil price for stock market risk as in Basher and Sadorsky (2006) and Sadorsky (2006).

Hamilton (1996; 2003) and Gronwald (2008), among others.[3] The research in the two areas is clearly connected, since oil prices shocks influence stock prices through affecting expected cash flows and/or discount rates. Oil prices shocks can affect corporate cash flow since oil is an input in production and because oil price changes can influence the demand for output at industry and national levels. Oil prices shocks can affect the discount rate for cash flow by influencing the expected rate of inflation and the expected real interest rate. The corporate investment decision can be affected directly by change in the latter and by changes in stock price relative to book value.

In recent work emphasis has been placed on the changing nature of the connection between oil prices and real activity. Blanchard and Gali (2007) find smaller effects of oil price shocks on macroeconomic variables in recent years. Kilian (2008b) reports that while exogenous oil supply shocks, identified as oil production disruptions, have a significant effect on the economy, their impact on the U.S. economy since the 1970s has been small compared to the impact of other factors. Along similar lines, Cologni and Manera (2009) report that the role of oil shocks in explaining recessions has decreased over time in G7 countries. This change in the relationship between oil prices and real activity in recent years from earlier decades is attributed to several causes including improvements in energy efficiency and in the conduct of monetary and fiscal authorities.

In this paper, we analyze the long-run relationship between the price of crude oil and international stock markets from January 1971 to March 2008 using a vector error correction model (VECM). The basic model we employ includes additional regressors to control for short-

[3] Cologni and Manera (2008), Kilian (2008a) Jimenez-Rodriguez and Sanchez (2005), Cunado and Perez de Garcia (2005) and Lee *et al.* (2001) have confirmed a negative link between oil price shocks and aggregate activity for other countries. Huntington (2005), Barsky and Kilian (2004) and Jones *et al.* (2004) provide reviews on the effect of oil shocks on the aggregate economy.

run dynamics between stock market prices for six OECD countries and a single international crude oil price and other macroeconomic series. The contribution of this paper is in the analysis of the long-run relationship between oil price and stock prices in a number of major countries jointly while allowing for short-run macroeconomic influences on stock price. This is in contrast to much recent work which has focused on the short-term impact of oil price increases on stock market returns.[4] Moreover, we allow for the possibility of endogenously identified structural breaks in both the long-run and short-run relationships.

We find a clear long-run relationship between these series for six OECD countries from 1971 until May 1980 and again from February 1988 until September 1999, suggesting that stock market indices respond negatively to increases in the oil price. Although we do not find long-run relationships to be statistically significant in the intervening period, they are not statistically significantly different from those in the previous period, either.[5]

The long-run relationship appears to disintegrate and even change signs in some cases after September 1999, based on data through March 2008. Such an empirical finding supports a conjecture, not only of a change in the relationship between oil prices and real variables in recent years from earlier decades, but possibly of several stock market bubbles and/or oil price bubbles since the turn of the century.

The remainder of the paper is structured as follows. In the following section, we provide a non-quantitative motivation for our analysis. Our econometric model and explanations of our

[4] The impact of oil price increases on stock market returns (and analysis of short-run effects) has been considered by Nandha and Faff (2008), O'Neil *et al.* (2008), Park and Ratti (2008), Ciner (2001) and Sadorsky (1999), as noted earlier. In other work, for example, Sadorsky (2001) and Boyer and Filion (2007) find that positive oil price shocks significantly raise stocks returns for Canadian oil and gas companies, El-Sharif *et al.* (2005) report a similar result for U.K. oil and gas companies, and Papapetrou (2001) reports that positive oil price shocks significantly reduce stock returns in Greece.

[5] In fact, if we omit the break in either 1980 or 1988, we find statistically significant negative relationships from January 1971 until January 1988 or from June 1980 until September 1999, respectively. The likelihood function is increased by including these breaks, but at the expense of statistical significance over the intervening period.

estimation technique and breakpoint identification procedure are contained in Section 3. Section 4 discusses specification test results, while Section 5 holds our main empirical results. Section 6 concludes. Data and sources are discussed in an appendix.

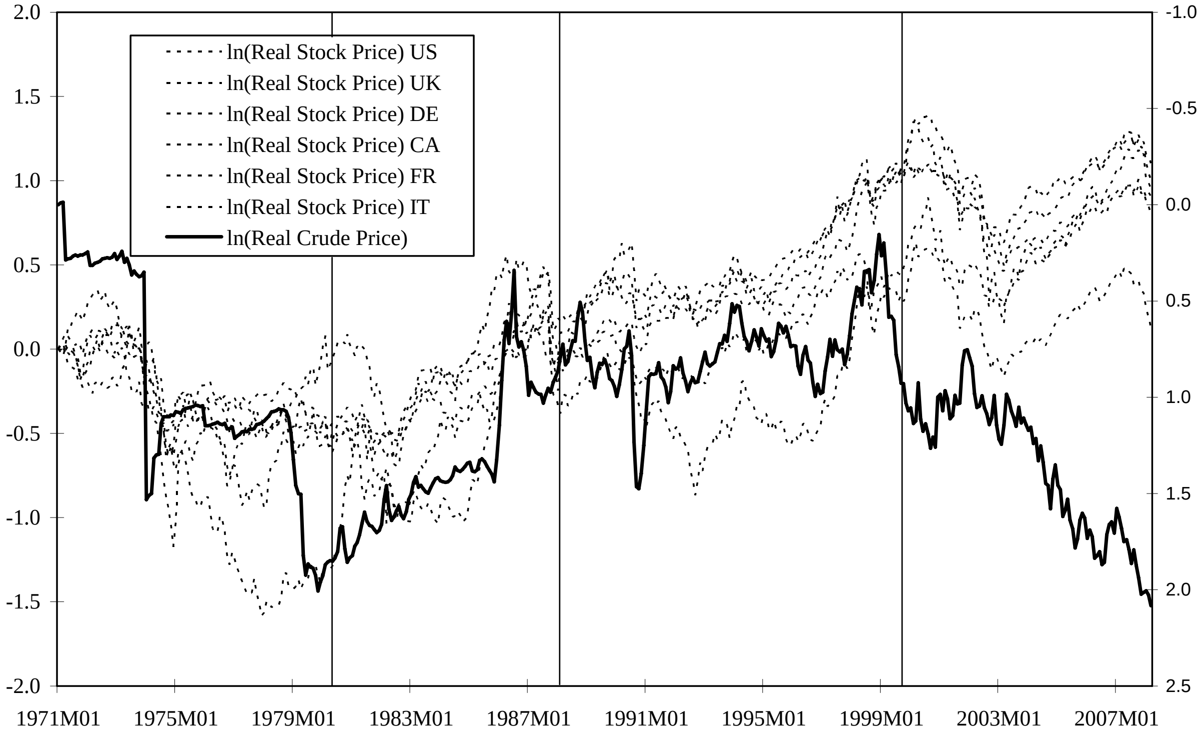
2. Motivation: End of the Oil Era or Beginning of the Bubble Era?

Figure 1 shows a simple time series plot of the real stock market prices and real crude oil prices[6] for six countries from January 1971 through March 2008, with crude oil measured on the *reversed* RHS axis. The countries are Canada, France, Germany, Italy, U.K. and U.S., designated by CA, FR, DE, IT, UK and US, respectively. The set of countries is chosen because they represent the major developed countries over a sample starting in 1971 and real stock prices and real crude oil price share a single stochastic trend. Japan is not included because the real stock price for Japan does not share this single stochastic trend. Up until about December 1998, the plot clearly indicates the presence of long-run relationships, with one or more common stochastic trends. Since the crude oil axis is reversed, such relationships imply that long run decreases in the price of oil correspond to long-run increases in stock market prices around the world, and vice versa.

After December 1998, when the oil price reached its historic low since the early 1970's, this price began to climb. Since early 2003, the climb in the real oil price has been steady and rapid. Unlike the early 1970's, stock market prices continued to climb – rather than decline as the preceding relationships suggest that they should. This casual observation stimulates doubt about the structural stability of these relationships after 1998, in line with the arguments advanced by a number of researchers that the relationship between oil prices and real economic variables has differed in the most recent decade from that in earlier years.

[6] The plot in Figure 1 shows the natural logarithm of these prices with each series normalized so that the first observation is zero. Throughout the remainder of the paper, we refer to these transformed series without further reference to the transformation. Data are discussed further in an appendix.

Figure 1: Stock Market Prices and the Crude Oil Price (Jan 1971 - Mar 2008)



Notes: LHS axis is for stock prices and RHS axis is for crude oil. Note that the RHS axis is REVERSED.
All series (log prices) normalized to start at zero.

The presence of a structural break sometime in 1999 may be explained by the now mostly uncontroversial presence of the so-called "IT bubble," which inflated stock markets around the turn of the century. The introduction of a speculative bubble could cause stock prices to continue to increase, even as oil prices begin to increase, as they did after 1998. The general consensus is that the IT bubble peaked in March 2000, and it seems to have dissipated by the end of 2002. Stock market prices may have reverted to the pre-bubble long-run trend at that time. Beginning in early 2003, however, stock markets began to climb once again, although the oil price continued to increase. Indeed, another anomaly in the relationship between real oil price and real stock prices becomes apparent in the data after 2003. The stock market downturn that began in the summer of 2007 did very little (as of March 2008) in the way of putting stock markets back on track with their apparent long-run relationships with oil prices before 1999.[7]

It is difficult to explain this apparent reversal of the long-run relationship. Improvements in energy efficiency in these economies, while significant, cannot affect such change as that observed in the relationship between the real oil price and real stock prices in the last decade.[8] Blanchard and Gali (2007) assert several reasons for the diminishing effect of oil prices on GDP, including efficiency, more flexible labor markets, improved monetary policy, and a lack of shocks.

A more feasible explanation for stock market prices lies in speculative bubbles. Perhaps investors still believe the increase in the oil price since 1998 – like those in 1979 and 1990 – is only temporary. The graph (and our econometric evidence below) suggests that a reassertion of the pre-1999 long-term relationship between real oil price and real stock markets would translate into a substantial decline in worldwide stock market prices if the real oil price remains at levels achieved in early 2008.

3. Econometric Model and Estimation

Due to the perceived presence of multiple cointegrating relationships in the data, the basic modeling framework we employ is a vector error correction model (VECM) with additional regressors. These additional regressors (first-differenced log interest rates and industrial production) are included to control for short-run dynamics between the time series of

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[7] It is interesting that the 1999 date for a structural break also coincides roughly with financial crisis and hard times in Asia, Russia and Brazil.

[8] An interesting contributing factor for the apparent change in the behavior of the data in the recent decade may be the prevalence of energy price subsidies in China (reduced substantially in June 2008) with the ongoing rise of Chinese exports. China has been subsidizing energy prices to stimulate their economy. In effect, the price of imported manufactured goods goes down in OECD countries because more parts are supplied by China, even though the price of oil is going up exogenously to stock markets (helped by Chinese subsidies). This transfer of production to a cheaper source partially insulated from energy prices is unlikely to be important enough to provide a gain in efficiency large enough to offset increasing energy prices and create bubbles in the data.

interest and other macroeconomic series. Specifically, changes in interest rates and industrial production allow us to control for demand shocks affecting stock market prices but not captured by short-run oil price changes. Sadorsky (1999) for the U.S. and Park and Ratti (2008) for the U.S. and European countries also consider the influence of first-differences of industrial production and interest rates (for each country separately), but do not allow for the *long-run* interaction between oil and stock market prices. We do not include these covariates in the cointegrating relationship, because we do not expect them to follow the same long-run trend as stock market prices.[9]

3.1 Econometric Model

We have stock market prices for N countries and a single international crude oil price. We let z_t denote the $(N+1)\times 1$ vector of these random variables observed over $t=1,...,T$. The family of VECMs based on those studied by Johansen (1988, 1995) may be written as

$$\Delta z_t = \Gamma_0 A_0' z_{t-1} + \sum\nolimits_{k=1}^{q-1} \Gamma_k \Delta z_{t-k} + B x_t + \mu d_t + \varepsilon_t \,, \qquad (1)$$

where A_0 is an $(N+1)\times r$ matrix of cointegrating vectors, Γ_0 is an $(N+1)\times r$ matrix of error correction coefficients, (Γ_k) are $(N+1)\times(N+1)$ (nuisance) parameter matrices, x_t is a $2N\times 1$ vector containing first-differenced log interest rates and industrial production for the N countries, B is an $(N+1)\times 2N$ (nuisance) parameter matrix, μd_t is a generic deterministic term, and ε_t is a normally distributed error term. As is standard in this type of model, the sequence (ε_t) is assumed to be independent and identically distributed.

[9] In a really large sample, it would not hurt to include these covariates in the cointegrating relationships. If they are not cointegrated, we would simply estimate more stochastic trends (fewer cointegrating relationships) in the VECM. However, inclusion of these covariates in the cointegrating matrix uses up a large number of degrees of freedom. We did not think the sample size large enough to justify relaxing this seemingly innocuous restriction, since previous empirical evidence (e.g., Park and Ratti, 2008) suggests that these are not cointegrated with stock market prices.

Much of the literature on parameter instability in cointegrated models relies on structurally stable cointegrating and error correction matrices, but focuses on structural breaks in the deterministic components of the cointegrating equations and the error correction equations. Gregory and Hansen (1996) developed early tests for stability of both deterministic and stochastic trends, but in non-autoregressive single-equation cointegrating regressions. Stability of deterministic trends in a cointegrated VAR/VECM has been analyzed by Johansen, Mosconi, and Nielsen (2000), Saikkonen and Lütkepohl (2000), and Lütkepohl, Saikkonen, and Trenkler (2004).

Rather than breaks in the deterministic trends, we wish to allow breaks in the stochastic trend(s) – i.e., cointegrating matrix, because we suspect a substantial change in the relationship near 1998. Our specifications tests (below) suggest that the model needs no more deterministic trends than an intercept, $d_t = 1$, which does not appear to change at this time. The model thus has two deterministic components: a non-zero mean in the differenced series (controlling for the covariates) and an intercept in the cointegrating relationship.

The nonzero mean in differences translates into a linear time trend in levels, but we find evidence against such a trend in the individual series. We are not concerned with structural breaks in a parameter that may be statistically superfluous.

A structural break in the intercept in the cointegrating relationship would correspond to a sudden shift in the difference between sample means of the series. It appears that such a break may have occurred in 1973 and/or 1979, because stock market prices did not fall sharply as oil prices increased sharply. Stock market prices declined sharply a few periods *after* the 1973 shock and more steadily after the 1979 shock. Consequently, the potential break in the intercept of the cointegrating relationship appears to be temporary, and could just as easily be explained by short-run disequilibrium error, which our model already captures.

We allow breaks in the stochastic trend(s) at unknown times τ_i for $i = 1,\ldots,b$, where b is the number of breaks. With the convention that $\tau_0 = 0$ and $\tau_{b+1} = T$, we may reparameterize the model as

$$\Delta z_t = \sum_{i=0}^{b} \Gamma_i A_i' z_{t-1} 1\{\tau_i < t \le \tau_{i+1}\} + \sum_{k=1}^{q-1} \Gamma_k \Delta z_{t-k} + Bx_t + \mu d_t + \varepsilon_t , \qquad (2)$$

where $1\{\cdot\}$ denotes the indicator function, taking a value of one if its argument is true and zero if false. Note that if $b = 0$, the model in (2) reduces to that in (1).

3.2 Estimation

Estimation of the model in (1) is straightforward and may be accomplished using standard software packages, such as STATA. The reader is referred to Johansen's (1995) text for details on reduced rank regression estimation of a VECM.

The entire system contains $(N+1)^2(q-1)$ nuisance parameters from lagged endogenous variables, $N+1$ nuisance parameters from constant terms, and $2N(N+1)$ nuisance parameters from regressing out contemporaneous changes in interest rates and industrial production. The cointegrating matrix and disequilibrium coefficients add $2(N+1)r$ parameters, but with r^2 restrictions. The whole system thus has

$$(N+1)[T-(N+1)(q-1)-1-2N-2r]+r^2$$

degrees of freedom. Since this is not generally divisible by $N+1$, we use the greatest integer not exceeding

$$T-(N+1)(q-1)-1-2N-2r+r^2/(N+1)$$

to approximate degrees of freedom for each equation in order to calculate standard errors.

Estimation of the structural break model in (2) is more complicated, even if the breakpoints are known. For known breakpoints, we may use an iterative procedure with preliminary estimates of A_i given by $\hat{A}_i^0 = \hat{A}$, where $\hat{A}$ comes from the restricted model (with no structural breaks) in (1). We may use these preliminary estimates to regress out $\hat{A}_i' z_{t-1} 1\{\tau_i < t \le \tau_{i+1}\}$ for all but *i = 0*, in order to estimate A_0 using reduced rank regression. This estimate $\hat{A}_0^1$ may then be used to obtain $\hat{A}_1^1, \ldots, \hat{A}_b^1$ sequentially. The whole procedure may then be iterated to obtain $\hat{A}_0^2$, $\hat{A}_1^2$,…, $\hat{A}_b^2$, etc., until convergence.[10] $\Gamma_0, \ldots, \Gamma_b$ are subsequently estimated. This procedure is similar to one described by Johansen (1995) for implementing multiple restrictions on a cointegrating matrix.

As with most numerical optimization routines, there is no guarantee that convergence will be achieved. The initial choice of $\hat{A}_i^0$ may not be close to cointegrating z_{t-1} during the respective time period. In the extreme, it may lie in the space orthogonal to the cointegrating space of z_{t-1}. In this case, we project out integrated regressors, rather than stationary regressors. The asymptotic results may not be similar.

However, as long as $\hat{A}_i^0$ has full column rank with the correct number of columns, collinearity should not be a problem. The moment matrix in the projection onto the space orthogonal to $\hat{A}_i' z_{t-1} 1\{\tau_i < t \le \tau_{i+1}\}$ should be invertible. It is reasonable to expect that, as long as the matrix inversion works, estimates of the cointegrating vectors will iteratively improve.

It would be straightforward to modify the procedure to allow for a break in the constant part of the cointegrating relationship. The vector z_{t-1} could simply be augmented with d_t .

[10] For practical implementation, we assume convergence when the maximum element in the matrix of differences from one iteration to the next falls below 10^{-6}.

Unlike with the standard VECM, this would not be collinear with the d_t already in the model, since the indicator function adds variation.

Finally, we note that with each structural break in the cointegrating matrix, an additional $2r - r^2/(N+1)$ degrees of freedom per equation are employed. Degrees of freedom corrections for standard errors in small samples are adjusted accordingly.

3.3 Endogenous Break Point Identification

We allow the break points to be determined endogenously by performing rolling likelihood ratio tests similar to those employed by Camarero and Tamarit (2002) using the testing procedure of Hansen and Johansen (1993). We start with a null of no breaks and calculate an LR test for a series of alternatives with break points from near the beginning of the sample rolling to near the end of the sample. We choose one or more break points where the series of LR test statistics reaches salient maxima, if the maxima are above the chi-squared critical value.

We then repeat this procedure with the new null incorporating the break points just chosen. The alternative is one more breakpoint, and additional points may be chosen by a similar rolling procedure with a buffer around the break points in the null, in order to allow sufficient degrees of freedom between breaks.[11] The procedure may be repeated until either no statistically significant break points are found or until the buffers allow no more alternatives.

4. Specification and Identification

Before presenting our main empirical findings, we more precisely specify the VECM model. We must choose the number and type of deterministic trends, the cointegrating rank, lag length, an appropriate identification scheme for the cointegrating space, and of course the break

[11] We chose the buffer to be $2r - r^2/(N+1) + 36$ in our empirical analysis in order to allow at least 36 degrees of freedom between each break. This choice is somewhat arbitrary, but did not appear to be a binding constraint in our empirical results.

points. We note that the specification tests in this section are conducted prior to modeling structural breaks in the cointegrating relationships. This priority does not affect any of the univariate tests, such as those for unit roots and deterministic trends in the individual series.

4.1 Deterministic Trends and Unit Roots Tests

Within the family of VECM's described above, there are five typical specifications for a deterministic trend in either levels of (z_t) or in the differenced model given by (1). In order to get a rough idea of which specification might be most appropriate, we conduct diagnostic tests on the individual series over the full sample, shown in Table 1.

The first and second columns of Table 1 show the estimate and standard error of an intercept in a first-order autoregression using the first difference of each series. These tests provide justification for the type of deterministic trend to be included in the subsequent unit root tests on the individual series (since the critical values depend on this) and in the VECM model itself. Under the maintained hypothesis that this first difference is either stationary or trend stationary, t-tests constructed from these are (asymptotically) normal. Clearly, we cannot reject a null of no intercept in differences, providing evidence *against* a linear trend in levels.

The third, fourth, and fifth column of Table 1 show results from unit root tests. Specifically, we conduct standard Phillips-Perron (1988) coefficient and t- tests and KPSS tests, including only a constant. (We omit a linear trend as suggested by the results of the autoregression in first differences.) We firmly reject stationarity of the crude oil price series and all of the stock market price series using the KPSS tests, and we fail to reject a unit root anywhere using the Phillips-Perron tests, evidence which clearly indicates the presence of nonstationarity.

In light of these preliminary tests, the most appropriate specification for our model seems to be a VECM specification with $d_t = 1$. We allow an unrestricted constant term so that a constant may be included in both the cointegrating equations and in the error correction equations. This allows a (perhaps unnecessary) linear trend in the r stationary combinations. Further restriction of this term does not seem to improve efficiency.

4.2 Cointegrating Rank and Lag Length

Determining the number of lags q and dimension r of the cointegration space can be challenging in such models, and usually requires some kind of prioritization of choices. To avoid this, we employ a semiparametric rank selection approach similar to Cheng and Phillips (2008).[12] They show analytically that information criteria such as the Hannan-Quinn criterion (HQ) and the log of the Hannan-Quinn criterion (lnHQ) consistently select the correct cointegrating rank. Their technique is robust to misspecification of the lag length in large samples. In order to deal with potential small-sample complications arising from a misspecified lag length, we construct three portmanteau-type information criteria for rank selection, using information from lag lengths one through sixteen. Specifically, we take a simple average of HQ across all lag lengths, a simple average of lnHQ across all lag lengths, and a simple average of both HQ and lnHQ across all lag lengths. For each rank r, we denote these by $IC_1(r)$, $IC_2(r)$, and $IC_3(r)$, respectively. We similarly create $IC_1(q)$, $IC_2(q)$, and $IC_3(q)$ by averaging HQ, lnHQ, and both HQ and lnHQ, respectively, across all ranks for each lag length q.[13]

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[12] The literature on rank selection using information criteria (IC) instead of likelihood ratio tests is well-established. See, for example, Gonzalo and Pitarkis (1998), Chao and Phillips (1999), Aznar and Salvador (2002), Kapetanios (2004), and Wang and Bessler (2005). A disadvantage of the traditional testing approach lies in the fact that there is always a positive probability of making a mistake (size and one minus power), even in large samples. A consistent IC (such as BIC, HQ, lnHQ) overcomes this problem in large samples, and a few of the papers mentioned above show favorable small-sample results for such IC. The semiparametric approach of Cheng and Phillips (2008) offers an additional advantage, in that the exact number of lags need not be chosen before the cointegration rank is selected.

[13] Our approach does not differ that much from Cheng and Phillips (2008). Those authors showed that HQ-type information criteria consistently select cointegrating rank with lag length set to one (the remaining lags are thus

Table 2 shows the information criteria calculated for ranks zero through N+1 (all possible ranks) and for lags one through sixteen for the full sample with no breaks. Minimal information criteria in each group are noted. $IC_1(r)$, $IC_2(r)$, and $IC_3(r)$ agree on only a single common trend (N cointegrating relationships).

The presence of at least one cointegrating relationship and at least one trend support reduced rank regression to estimate the VECM, rather than standard estimation of a VAR in levels or differences. Our results suggest that all seven series (real crude oil price and six stock market prices) share a *single* common stochastic trend. The rank tests thus provides evidence for cointegration between the stock prices in our sample and is consistent with findings of capital markets integration noted by Korajczyk (1996) and Forbes and Rigobon (2002). This finding contrasts with that of Ahlgren and Antell (2002), for example, who find little evidence for cointegration of international stock prices. Ahlgren and Antell (2002) use standard Johansen rank tests and note the sensitivity of their results to pre-test lag selection. Our semiparametric rank selection criteria are consistent and robust to misspecification of lag length (at least in large samples). Also, Ahlgren and Antell (2002) consider a different set of countries (Finland, France, Germany, Sweden, the U.K. and the U.S.) and a different sample period (January 1980 to February 1997).

Lag selection is more complicated, since selection criteria suggest two, fifteen, and sixteen (the maximum) lags. We choose the most parsimonious specification of these: two lags. Parsimonious lag selection reserves degrees of freedom for endogenous selection of structural breaks.

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nonparametrically specified). Their large-sample results should reasonably hold for any fixed lag length, and the small-sample properties should be improved by fixing at some number higher than one, since this naturally removes some serial correlation from the error term. Using information criteria to choose the lag with rank fixed (to be full) is a more traditional approach. We take the average IC across all ranks so that the procedure is more robust to rank deficiency.

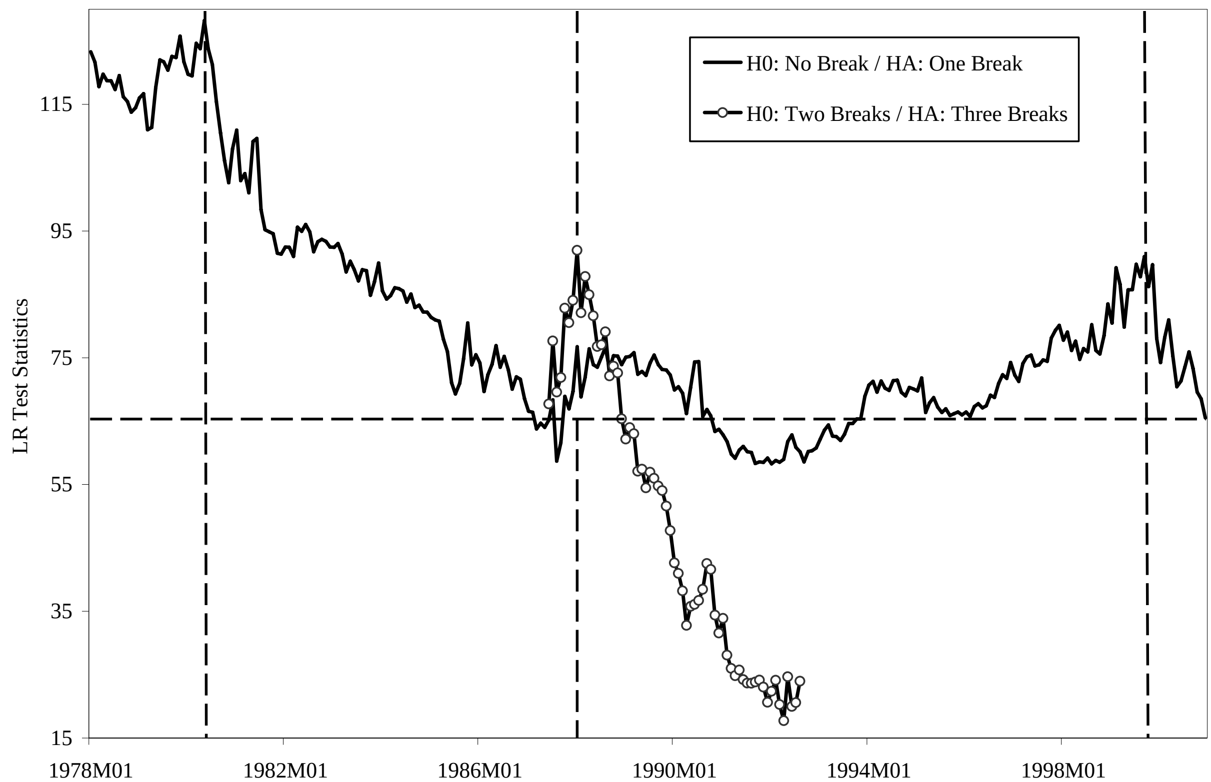
4.3 Break Points

We select break points using the technique discussed above. Time series plots of the rolling likelihood ratio tests are given in Figure 2. The null of no break is rejected against a large number of alternatives. The most salient rejections occur for breaks after May 1980 and September 1999. We then iterate the procedure with a null of breaks only at these points. The null is rejected against fewer alternatives, with the most salient rejection after January 1988. Based on our criterion described above, there are insufficient degrees of freedom to effectively identify additional breakpoints.

4.4 Identification of the Cointegrating Space

Having chosen the number of deterministic trends, the cointegrating rank, the number of lags, and the location of the structural breaks, we need only choose an identification scheme for A. We sort the equations with stock market prices first and the crude oil price last and then restrict the first r columns of A (corresponding to the N stock market prices) to be an identity matrix, an identification scheme suggested by Johansen (1995). This identifying restriction is natural, since the information criteria discussed above suggest that the last series (crude oil price) is cointegrated with each of the first r series (stock market prices), which are jointly cointegrated. Note that since identification of the cointegrating space occurs *after* testing and estimation, it does not affect the likelihood function.

Figure 2: Rolling Likelihood Ratio Test Statistics for Structural Breaks



4.5 Potential Asymmetries

Ciner (2001) and others note that the relationship between oil price shocks and stock prices may be nonlinear. We believe that observed nonlinearities in the long-run relationship could result from structural breaks in an otherwise linear relationship, such as our model employs. Asymmetries in the short-run relationship should not affect our estimates of the long-run relationship (our parameters of interest) substantially, but the nuisance parameter estimates could be affected. Asymmetries in the long-run relationship are possible. After 1979, oil prices steadily but stochastically declined until 1999, while stock market prices steadily but stochastically increased. Beginning in 1999, oil prices began steadily increasing, while stock market prices (at first) continued to increase. Alternatively to our simple structural breaks, asymmetry in the long-run response could be explicitly modeled. In that case, we would expect that while oil prices were increasing during the 1970's, the asymmetric response of stock market prices would cause them to *increase* during the 1970's. Since the relationship does not appear to change signs in the 1970's as it does in the 2000's, explicitly modeling asymmetry would require a structural break in the asymmetric behavior.

5. Main Empirical Results

For comparison, we first estimate the model with no structural breaks. We then estimate the model with the three breaks identified above (May 1980, January 1988, and September 1999). The results of the first estimation are given in Table 3, while those of the four periods of the second estimation are given in Tables 4-7. We omit nuisance parameter estimates for brevity.

Estimates of the short-run coefficients are less robust than those of long-run coefficients to misspecification of the number of lags. The robustness of the long-run estimates comes from the well-known superconsistency of the respective estimators, which may overcome asymptotic bias from this type of misspecification. Since the short-run estimates have only root-T convergence in a correctly specified model, they are more sensitive to misspecification of the stationary covariates (such as number of lagged differences). Since common practice for *any* vector time series model is to restrict the number of lags to be the same for every series, superfluous lags in some series may render short-run coefficients insignificant, while omitted lags in another series may switch the sign of the estimate.

Note that *positive* estimates of the non-unit, non-zero elements of the cointegrating matrix denote *negative* long-run relationships, and vice versa.

5.1 January 1971 – March 2008 (No Breaks)

Allowing no structural breaks does not yield any statistically significant long-run relationship between stock market and crude oil prices. Moreover, the negative sign is the opposite of what we expect, suggesting that long-run changes in the crude oil price are accompanied by long-run changes in stock prices *in the same direction*. Note that this does not mean crude oil follows a separate stochastic trend – consistent information criteria suggest only one common stochastic trend. However, lack of significance clearly indicates uncertainty about the magnitudes and signs of the cointegrating coefficients.

5.2 January 1971 – May 1980

All estimated long-run parameters during this period have the expected positive sign. Long-run changes in the crude oil price are therefore accompanied by long-run changes in stock prices in the opposite direction, as expected. We find these coefficients to be statistically significant for the U.S., the U.K., Germany, and Italy.

Moreover, a number of the short-run adjustment coefficients are statistically significant. For example, when Italian stock market is out of equilibrium with the world crude oil price, such that the Italian stocks are overvalued, statistically significant parameter estimates suggest that the Italian stock market price should adjust downwards, the crude oil price should adjust downwards, or the U.K. stock market price should adjust downwards, all else being equal. In fact, if any of the six stock markets are overvalued relative to the oil price, the respective stock market will adjust downwards in the short run. However, this relationship is only significant for Italy, Canada, and the U.K.

5.3 June 1980 – January 1988

In contrast, none of the long-run relationships are statistically significant during this period, even though all but Canada have the expected positive sign. Canada is very close to zero, but the negative sign no doubt results from a precipitous – but perhaps idiosyncratic – decline in the Canadian stock market during the early part of this period. On the other hand, none are statistically significantly different from the parameter estimates of the 1971-1980 period, suggesting the possibility that the structural break in 1980 was limited to the short-run coefficients.

Without significant long-run relationships, it is difficult to interpret short-run dynamics. However, a few of them are significant with the correct sign. Similarly to the previous period, the stock markets adjust downwards in the short-run if overvalued relative to crude oil, except for Germany. This relationship is significant for Italy, France, and Canada.

5.4 February 1988 – September 1999

During the third period, *all* of the long-run relationships are significant with the expected positive sign. This period featured steadily growing stock markets, except for the Italian stock market around 1992 (probably due to speculative attacks on the Lira at about that time), and steadily declining oil prices, except during the Gulf War.

Some of the short-run dynamics are significant with the expected sign. Similarly to previous periods, all of the stock markets adjust downwards in the short-run if overvalued relative to crude oil, with a significant coefficient for Italy and Germany.

None of the short-run adjustments of the crude oil price to the equilibrium relationships with stock market prices are significant. The supposed exogeneity of this series may account for this result. The Italian stock market, for example, would more reasonably adjust downwards to correct an imbalance with the world oil price than would the world oil price adjust downwards to correct the imbalance.

5.5 September 1999 – May 2008

During the last period, the long-run relationships are mostly insignificant, with the U.S. and Canada having the wrong sign. The counter-intuitive sign for Canada is even significant. Even the positive coefficients are substantially smaller than in the previous period. These results suggest a break in 1999 so substantial that the natural, prevailing long-run relationship fell apart or was even reversed.

5. Concluding Remarks

We analyze the long-run relationship between the world price of crude oil and international stock markets over the period from January 1971 to March 2008. We utilize a cointegrated vector error correction model with additional macroeconomic variables as regressors to capture short-term influences. Our technique allows for endogenously identified structural breaks in the cointegrating matrix and error correction matrix.

We find a clear long-run relationship between real stock prices for six OECD countries and world real oil price from January 1971 until May 1980 and again from February 1988 and September 19998, with positive statistically significant cointegrating coefficients for real stock market prices and the real oil price. Intuitively, this means stock market prices increase as the oil price decrease or decrease as the oil price increase, over the long-run. These results are natural in light of modern economies' reliance on oil at all levels of economic activity.

Between May 1980 and February 1988, the relationship is no longer significant. It should be noted, however, that although these estimates are not statistically significantly different from zero, neither are they statistically significantly different from the estimates of the previous period.

After September 1999, a more substantial break is apparent, with even a sign reversal in some cases. Overall, the stability of the long-run relationship between crude oil and stock market prices over the pre-1999 period with the subsequent disintegration or reversal of this relationship suggests that stock markets have not responded to oil prices in the expected way since then. Such an empirical finding supports a conjecture of change in the relationship between real oil price and real stock prices in the last decade compared to earlier years and the presence of several stock market bubbles and/or oil price bubbles since the turn of the century.

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Appendix: Data Sources

Data are monthly from January 1971 through March 2008. We construct a single world real crude oil price by subtracting the log of the U.S. PPI for all commodities from the log of the nominal price of U.K. Brent (a U.S. dollar index). Real stock market prices for six countries, CA, FR, DE, IT, UK and US, are created in a similar way using the respective countries' CPIs. We also use the log of 100 plus nominal short-term interest rates and the log of real industrial production for each country. All series are normalized so that the initial values are zero.

The sources of our raw data are as follows:

Nominal Oil Price: U.K. Brent from IFS, International Monetary Fund, (11276AADZF).

Producer Price Index (All Commodities): FRED, FRB of St. Louis (PPIACO).

Stock Market Prices: S&P 500 (US), and Main Economic Indicators, OECD (other countries).

Consumer Price Indices: Main Economic Indicators, OECD.

Industrial Production Indices: Main Economic Indicators, OECD.

Short-term Interest Rates:

- **US:** 3-month Treasury-bill rate from FRED, FRB of St. Louis (TB3MS).
- **DE:** Money market rates reported by Frankfurt banks / Three-month funds / Monthly average, German Federal Bank.
- **UK:** Treasury bill rate, IFS (line 60c), International Monetary Fund.
- **IT:** money market rate, IFS (line 60c), International Monetary Fund.
- **FR:** money market rate, National Institute for Statistics and Economic Studies (INSEE).
- **CA:** short term rate (three month maturity), OECD.

Table 1: Diagnostic Tests on the Individual Series

	t-tests			Z(c)	Z(t)	KPSS
	Int	(s.e.)	(c.v.)	-14.1	-2.86	0.463
ΔS_{US}	0.0025	0.0017	S_{US}	0.221	-0.093	7.728 **
ΔS_{UK}	0.0018	0.0022	S_{UK}	-1.199	-0.909	7.197 **
ΔS_{DE}	0.0021	0.0025	S_{DE}	-1.671	-0.890	7.175 **
ΔS_{CA}	0.0020	0.0022	S_{CA}	-1.280	-0.570	6.397 **
ΔS_{FR}	0.0022	0.0027	S_{FR}	-0.979	-0.654	7.204 **
ΔS_{IT}	0.0003	0.0028	S_{IT}	-2.505	-1.391	4.390 **
ΔCrude	0.0047	0.0045	Crude	-10.147	-2.393	0.811 **

Int: Intercept estimate from a first-order autoregression of *first differenced* series;
Z(c) and Z(t): Phillips-Perron unit root coefficient tests and t-tests (unit root null, intercept only); and
KPSS: KPSS unit root tests (stationary null, intercept only).
Only significance at 5% size noted.

Table 2: Information Criteria for Rank and Lag Selection

Rank	$IC_1(r)$	$IC_2(r)$	$IC_3(r)$	Lag	$IC_1(q)$	$IC_2(q)$	$IC_3(q)$
0	-43.214	-44.490	-43.852	1	-43.249	-43.583	-43.416
1	-43.263	-44.575	-43.919	2	-43.599 **	-44.068	-43.833
2	-43.276	-44.619	-43.947	3	-43.539	-44.143	-43.841
3	-43.283	-44.651	-43.967	4	-43.494	-44.233	-43.863
4	-43.284	-44.672	-43.978	5	-43.429	-44.305	-43.867
5	-43.286	-44.687	-43.987	6	-43.402	-44.414	-43.908
6	-43.287 **	-44.696 **	-43.992 **	7	-43.343	-44.493	-43.918
7	-43.283	-44.695	-43.989	8	-43.360	-44.648	-44.004
				9	-43.325	-44.752	-44.039
				10	-43.235	-44.801	-44.018
				11	-43.165	-44.871	-44.018
				12	-43.115	-44.962	-44.038
				13	-43.080	-45.067	-44.074
				14	-43.070	-45.199	-44.134
				15	-43.017	-45.289	-44.153 **
				16	-42.928	-45.343 **	-44.136

Information criterion for rank selection (left panel) and lag selection (right panel).
Information criteria calculated as
$IC_1(r)$: Average of HQ across all lags *q* for rank *r*;
$IC_2(r)$: Average of lnHQ across all lags *q* for rank *r*;
$IC_3(r)$: Average of both HQ and lnHQ across all lags *q* for rank *r*;
$IC_1(q)$: Average of HQ across all ranks *r* for lag *q*;
$IC_2(q)$: Average of lnHQ across all ranks *r* for lag *q*; and
$IC_3(q)$: Average of both HQ and lnHQ across all ranks *r* for lag *q*.
Minimal criterion in each column noted with two asterisks.

Table 3: Jan 1971 – Mar 2008 (No Structural Break)

LR	CE_1	(s.e.)	CE_2	(s.e.)	CE_3	(s.e.)	CE_4	(s.e.)	CE_5	(s.e.)	CE_6	(s.e.)
S_{US}	1		0		0		0		0		0	
S_{UK}	0		1		0		0		0		0	
S_{DE}	0		0		1		0		0		0	
S_{CA}	0		0		0		1		0		0	
S_{FR}	0		0		0		0		1		0	
S_{IT}	0		0		0		0		0		1	
Crude	-1.661	1.174	-1.284	1.031	-1.226	0.938	-1.373	0.738	-1.668	1.254	-1.422	0.916
SR	CE_1	(s.e.)	CE_2	(s.e.)	CE_3	(s.e.)	CE_4	(s.e.)	CE_5	(s.e.)	CE_6	(s.e.)
S_{US}	-0.003	0.023	0.026	0.018	-0.015	0.017	-0.013	0.026	0.009	0.019	-0.011	0.011
S_{UK}	0.015	0.028	-0.003	0.022	0.000	0.021	-0.003	0.032	0.002	0.023	-0.020	0.014
S_{DE}	0.035	0.038	0.050	0.030	-0.062	0.028 **	-0.023	0.043	-0.013	0.031	-0.004	0.019
S_{CA}	0.053	0.034	0.022	0.026	-0.022	0.025	-0.046	0.038	-0.016	0.028	-0.010	0.016
S_{FR}	0.064	0.039	0.032	0.030	0.022	0.029	-0.037	0.044	-0.093	0.032 **	0.018	0.019
S_{IT}	-0.079	0.037 **	0.063	0.029 **	-0.045	0.027	0.103	0.041 **	0.044	0.030	-0.068	0.018 **
Crude	0.045	0.066	-0.094	0.052	-0.009	0.049	0.054	0.075	0.024	0.054	-0.012	0.032

Estimates of matrix of cointegrating vectors *A* (LR relationships) and error correction matrix Γ (SR adjustments to the LR relationships) for full sample using standard reduced rank regression. CE denotes the *r* cointegrating equations. *A* normalized for identification. Only significance at 5% size noted.

Table 4: Jan 1971 – May 1980 Estimates

LR	CE_1	(s.e.)	CE_2	(s.e.)	CE_3	(s.e.)	CE_4	(s.e.)	CE_5	(s.e.)	CE_6	(s.e.)
S_{US}	1		0		0		0		0		0	
S_{UK}	0		1		0		0		0		0	
S_{DE}	0		0		1		0		0		0	
S_{CA}	0		0		0		1		0		0	
S_{FR}	0		0		0		0		1		0	
S_{IT}	0		0		0		0		0		1	
Crude	0.364	0.049 **	0.545	0.086 **	0.226	0.026 **	0.121	0.117	0.266	0.160	0.602	0.277 **
SR	CE_1	(s.e.)	CE_2	(s.e.)	CE_3	(s.e.)	CE_4	(s.e.)	CE_5	(s.e.)	CE_6	(s.e.)
S_{US}	-0.081	0.049	0.030	0.025	0.058	0.059	-0.140	0.049 **	0.116	0.045 **	-0.004	0.020
S_{UK}	0.009	0.060	-0.085	0.031 **	0.115	0.073	-0.026	0.060	0.141	0.055 **	-0.074	0.024 **
S_{DE}	-0.030	0.078	0.007	0.040	-0.129	0.095	0.014	0.079	0.001	0.072	-0.014	0.032
S_{CA}	-0.145	0.070 **	0.100	0.036 **	-0.003	0.085	-0.158	0.071 **	0.142	0.065 **	-0.027	0.028
S_{FR}	-0.241	0.080 **	0.067	0.041	0.059	0.098	0.134	0.081	-0.083	0.075	0.002	0.033
S_{IT}	-0.015	0.077	0.026	0.039	-0.054	0.093	-0.010	0.077	0.147	0.071 **	-0.071	0.031 **
Crude	-0.228	0.137	0.038	0.070	-0.567	0.167 **	0.125	0.138	0.286	0.127 **	-0.203	0.055 **

Estimates of matrix of cointegrating vectors *A* (LR relationships) and error correction matrix Γ (SR adjustments to the LR relationships) for sub-period, allowing for endogenously-chosen structural breaks using iterative reduced rank regression with the whole sample. CE denotes the *r* cointegrating equations. *A* normalized for identification. Only significance at 5% size noted.

Table 5: Jun 1980 – Jan 1988 Estimates

LR	CE_1	(s.e.)	CE_2	(s.e.)	CE_3	(s.e.)	CE_4	(s.e.)	CE_5	(s.e.)	CE_6	(s.e.)
S_{US}	1		0		0		0		0		0	
S_{UK}	0		1		0		0		0		0	
S_{DE}	0		0		1		0		0		0	
S_{CA}	0		0		0		1		0		0	
S_{FR}	0		0		0		0		1		0	
S_{IT}	0		0		0		0		0		1	
Crude	0.134	0.184	0.056	0.311	0.036	0.384	-0.006	0.157	0.278	0.292	0.362	0.290
SR	CE_1	(s.e.)	CE_2	(s.e.)	CE_3	(s.e.)	CE_4	(s.e.)	CE_5	(s.e.)	CE_6	(s.e.)
S_{US}	-0.147	0.106	-0.003	0.058	0.046	0.028	0.044	0.059	0.019	0.031	-0.006	0.016
S_{UK}	-0.034	0.130	-0.086	0.071	0.060	0.034	-0.013	0.073	0.025	0.038	-0.001	0.020
S_{DE}	-0.273	0.167	0.130	0.092	0.043	0.044	0.188	0.094 **	-0.111	0.049 **	-0.011	0.025
S_{CA}	0.275	0.151	-0.169	0.083 **	0.048	0.040	-0.182	0.085 **	0.051	0.045	-0.044	0.023
S_{FR}	0.084	0.174	-0.087	0.095	0.186	0.046 **	0.057	0.097	-0.208	0.051 **	-0.028	0.026
S_{IT}	-0.053	0.164	-0.173	0.090	0.114	0.043 **	0.068	0.092	0.111	0.048 **	-0.091	0.025 **
Crude	-0.187	0.297	0.097	0.163	-0.030	0.078	0.010	0.166	0.036	0.088	0.020	0.045

Estimates of matrix of cointegrating vectors *A* (LR relationships) and error correction matrix Γ (SR adjustments to the LR relationships) for sub-period, allowing for endogenously-chosen structural breaks using iterative reduced rank regression with the whole sample. CE denotes the *r* cointegrating equations. *A* normalized for identification. Only significance at 5% size noted.

Table 6: Feb 1988 – Sep 1999 Estimates

LR	CE_1	(s.e.)	CE_2	(s.e.)	CE_3	(s.e.)	CE_4	(s.e.)	CE_5	(s.e.)	CE_6	(s.e.)
S_{US}	1		0		0		0		0		0	
S_{UK}	0		1		0		0		0		0	
S_{DE}	0		0		1		0		0		0	
S_{CA}	0		0		0		1		0		0	
S_{FR}	0		0		0		0		1		0	
S_{IT}	0		0		0		0		0		1	
Crude	3.319	1.320 **	2.328	0.959 **	1.979	0.825 **	1.641	0.536 **	1.865	0.860 **	1.435	0.449 **
SR	CE_1	(s.e.)	CE_2	(s.e.)	CE_3	(s.e.)	CE_4	(s.e.)	CE_5	(s.e.)	CE_6	(s.e.)
S_{US}	-0.038	0.033	0.070	0.059	0.033	0.041	0.006	0.036	-0.042	0.039	-0.013	0.021
S_{UK}	0.003	0.041	-0.046	0.073	0.039	0.051	0.042	0.044	0.009	0.048	-0.035	0.026
S_{DE}	-0.075	0.053	0.195	0.095 **	-0.169	0.066 **	0.085	0.057	0.003	0.062	0.041	0.034
S_{CA}	-0.031	0.048	0.152	0.086	-0.094	0.059	-0.030	0.052	-0.011	0.056	0.010	0.031
S_{FR}	-0.067	0.055	0.207	0.097 **	-0.036	0.067	0.012	0.058	-0.117	0.064	0.050	0.035
S_{IT}	-0.094	0.052	0.028	0.093	0.017	0.064	0.143	0.056 **	0.038	0.061	-0.085	0.033 **
Crude	-0.162	0.095	0.268	0.169	-0.023	0.117	-0.137	0.101	0.052	0.111	0.014	0.060

Estimates of matrix of cointegrating vectors *A* (LR relationships) and error correction matrix Γ (SR adjustments to the LR relationships) for sub-period, allowing for endogenously-chosen structural breaks using iterative reduced rank regression with the whole sample. CE denotes the *r* cointegrating equations. *A* normalized for identification. Only significance at 5% size noted.

Table 7: Oct 1999 – Mar 2008 Estimates

LR	CE_1	(s.e.)		CE_2	(s.e.)		CE_3	(s.e.)		CE_4	(s.e.)		CE_5	(s.e.)		CE_6	(s.e.)	
S_{US}	1			0			0			0			0			0		
S_{UK}	0			1			0			0			0			0		
S_{DE}	0			0			1			0			0			0		
S_{CA}	0			0			0			1			0			0		
S_{FR}	0			0			0			0			1			0		
S_{IT}	0			0			0			0			0			1		
Crude	-0.078	0.433		0.196	0.572		0.036	0.555		-0.410	0.151	**	0.138	0.665		0.007	0.296	
SR	CE_1	(s.e.)		CE_2	(s.e.)		CE_3	(s.e.)		CE_4	(s.e.)		CE_5	(s.e.)		CE_6	(s.e.)	
S_{US}	-0.065	0.087		0.150	0.125		-0.084	0.057		0.075	0.081		-0.024	0.109		-0.011	0.069	
S_{UK}	0.036	0.107		0.046	0.153		-0.073	0.070		-0.007	0.100		-0.026	0.133		0.056	0.084	
S_{DE}	0.041	0.136		0.948	0.194	**	-0.289	0.089	**	0.316	0.127	**	-0.750	0.169	**	0.218	0.107	**
S_{CA}	0.044	0.126		0.317	0.179		0.005	0.082		-0.005	0.117		-0.319	0.156	**	0.046	0.099	
S_{FR}	-0.071	0.143		0.568	0.204	**	-0.051	0.093		0.201	0.133		-0.430	0.177	**	-0.005	0.112	
S_{IT}	-0.118	0.135		0.359	0.193		-0.028	0.088		0.163	0.126		-0.207	0.168		-0.094	0.106	
Crude	0.342	0.242		-0.168	0.345		0.065	0.158		0.462	0.225	**	-0.078	0.300		-0.326	0.190	

Estimates of matrix of cointegrating vectors *A* (LR relationships) and error correction matrix Γ (SR adjustments to the LR relationships) for sub-period, allowing for endogenously-chosen structural breaks using iterative reduced rank regression with the whole sample. CE denotes the *r* cointegrating equations. *A* normalized for identification. Only significance at 5% size noted.